Structural Equation Modeling: A Multidisciplinary Journal

ISSN: 1070-5511 (Print) 1532-8007 (Online) Journal homepage: http://www.tandfonline.com/loi/hsem20

Viability of exploratory factor analysis as a precursor to confirmatory factor analysis

David W. Gerbing & Janet G. Hamilton

STRUCTURAL EQUATION MODELING, *3*(1), 62–72

Viability of Exploratory Factor Analysis as a Precursor to Confirmatory Factor Analysis

David W. Gerbing and Janet G. Hamilton
School of Business Administration
Portland State University

As part of the development of a comprehensive strategy for structural equation model building and assessment, a Monte Carlo study evaluated the effectiveness of different exploratory factor analysis extraction and rotation methods for correctly identifying the known population multiple-indicator measurement model. The exploratory methods fared well in recovering the model except in small sample sizes with highly correlated factors, and even in those situations most of the indicators were correctly assigned to the factors. Surprisingly, the orthogonal varimax rotation did as well as the more sophisticated oblique rotations in recovering the model, and generally yielded more accurate estimates. These results demonstrate that exploratory factor analysis can contribute to a useful heuristic strategy for model specification prior to cross-validation with confirmatory factor analysis.

Until the 1980s researchers routinely analyzed latent variables (factors) and their relations to measured variables with a family of procedures called *factor analysis* (e.g., Harman, 1976; Mulaik, 1972 Thurstone, 1931). Now called *exploratory factor analysis* (EFA), typical practice involved submitting an intercorrelation matrix of indicators (e.g., items) to the factor analysis program contained in a statistical package such as SAS (SAS Institute Inc., 1989). With no model specification other than perhaps the number of factors, the procedure automatically extracts the factors and then rotates the solution to achieve a more meaningful interpretation. The chosen rotation either maintained uncorrelated factors (orthogonal) or allowed the factors to correlate (oblique).

Requests for reprints should be sent to David W. Gerbing, School of Business Administration, Portland State University, Portland, OR 97207–0751.

Confirmatory factor analysis (CFA), typically accomplished with maximum likelihood estimation (ML) as implemented with programs such as LISREL (Jöreskog & Sörbom, 1989) or EQS (Bentler, 1985), extends on this earlier method by providing a means for rigorously testing a model that must be specified a priori. Extending well beyond the simple specification of the number of factors, CFA requires a specification of the complete factor pattern, including the factor correlations. Specific values can be specified, or, more common, only the relations are specified with the corresponding parameter values estimated by the algorithm.

CFA is a more recent application than that provided by the exploratory or "blind" factor procedures. Although the conceptual distinction between the two techniques is well-known, little empirical work exists that compares them. However, both confirmatory and exploratory approaches would appear to offer comparative advantages and disadvantages depending on the situation. When the underlying structure of the measures (indicators) is not well understood, EFA's lack of a priori specification becomes a relative strength.

An underlying theme of this article is to not abandon EFA for the more recently developed confirmatory methods, but to develop a heuristic strategy that builds on the comparative strengths of the two techniques. This article analyzes the viability of a middle ground that incorporates methodology intermediate to pure exploratory and pure confirmatory methods. The goal is to develop a comprehensive strategy for model construction, evaluation, and revision that explicitly recognizes that models are developed from an interplay of theory and data. The thesis underlying this work is that the means for evaluating the fit of a model is a task distinct from the construction of the model. Specifically, to what extent can EFA serve as a heuristic device to construct measurement models that can be subsequently validated (including cross-validation on new data) with confirmatory methods?

It is always preferred to begin an analysis as far along the confirmatory end of the continuum as possible, and it is for the formal confirmatory analysis of models that most structural equation modeling research has focused. Because well-fitting models are almost always constructed from both theory and data, effective heuristic strategies for data driven model respecification are needed by the substantive researcher. Indeed, one implicit heuristic strategy has been the use of CFA/ML itself. In the presence of extensive respecification on the same data, modification indexes, standard errors, and global fit indexes are only heuristic guides instead of formal statistical statements. For statistical hypothesis testing of a model that has been extensively respecified on the same data, cross-validation on new data is both desirable and necessary.

Moreover, the methods provided by CFA for data-driven model respecification are more appropriate for "fine tuning" of the model than for large-scale respecification of severely misspecified initial models (Anderson & Gerbing, 1982; Gerbing, Hamilton, & Freeman, 1994). Because the consequences of localized specification errors from CFA/ML analysis become entangled throughout all parameter estimates, multiple misspecification errors interact with each other, obfuscating interpretability and respecification (Anderson & Gerbing, 1982). Further, CFA/ML requires substantial computation time. Severely misspecified, large models with many indicators that require tens of respecifications may require extensive amounts of time to respecify, each specification requiring many hours (Gerbing & Hamilton, 1994).

The analysis of the viability of an alternative heuristic strategy for successful model construction with EFA is the goal of this article. The primary question is how well different types of EFA extraction and rotation procedures affect the recovery of the form of a correctly specified multiple-indicator measurement model (each indicator is causally consequent to only a single latent variable or factor, and each factor is defined by at least two indicators). That is, how effectively do various EFA methods identify the model by correctly linking the indicators with the factors so that the correct structure of the model is specified for subsequent analysis by CFA? Also of interest is the relative accuracy of the parameter estimates computed by CFA and the EFA methods.

Consistent with the situation in which the substantive researcher knows the correct number of factors but not the underlying factor pattern or factor correlations, the correct number of factors is assumed to be known and specified in each EFA analysis. This choice was made because the problem of empirically determining the number of factors has been extensively studied elsewhere (Hakstian, Rogers, & Cattell, 1982). Further, a variety of techniques are available for assessing the number of factors, including the traditional eigenvalues structure as well as a comparison of under-factorial and over-factorial solutions, as well as the structure of the proportionality coefficients (Anderson & Gerbing, 1988) and an analysis of their content (Hunter, 1973). A comprehensive study of all of these methods is a related topic of interest but beyond the scope of this study.

METHOD

Models

Monte Carlo analyses of two different types of multiple-indicator population models were conducted: three versions of a synthetic model and a model obtained from an empirical analysis of impulsivity measures (Gerbing, Ahadi, & Patton, 1987). Each version of the synthetic model has 16 indicators partitioned into four factors with 4 indicators per factor. The loadings of the respective indicators are always .5, .7, .7, and .9, with factor variances set at 1.0. To approximately mirror the wide range of factor correlations encountered in actual research, the factor correlations varied from .2 to .8. In one version of the synthetic model (Synthetic .2) all factors correlate .2, and in the alternate versions all factors correlate .6 (Synthetic .6) or .8 (Synthetic .8).

The empirically validated impulsivity model—including cross-validation—has 44 indicators (Gerbing et al., 1987). The estimated pattern coefficients and factor correlations from the CFA/ML analysis of this model were the population values for purposes of data generation. Pattern coefficients ranged from a low of .59 to a high of .97. Two of the 14 factors had 2 indicators, 9 factors were operationalized by 3 indicators, 2 factors had 4 indicators, and 1 factor had 5 indicators.

Data

A Fortran program was written that uses IMSL (1980) subroutines to simulate sampling from a multivariate normal distribution as specified by one of the three corresponding population correlation matrices. Samples were generated of size 100 and 300 for each of the three models. One hundred data sets were generated for each of the six model–sample size combinations (cells) in the design. To facilitate interpretation and comparability, the generated data were transformed so that each data value was deviated from its corresponding population parameter value. For these transformed data, the expected value of an unbiased estimator was zero.

Procedure

The indicator correlations of each set of sample data were analyzed according to the (a) corresponding correctly specified model with the CFA/ML analysis provided by the LISREL VII program (Jöreskog & Sörbom, 1989), and (b) EFA using the SAS PROC FACTOR program (SAS Institute Inc., 1989) with the correct number of factors specified. The CFA/ML analysis was conducted first. Data were generated for each of the eight model–sample size combinations in the design until 100 sample variance–covariance matrices were obtained that yielded converged and proper CFA/ML solutions.

A variety of EFA methods were used in this study. EFA factors were extracted with the widely used principal factors (PF) method (i.e., derived from a components analysis with iterated communalities in the diagonal), as well as ML. PF was included in this study because it is the most widely used method. ML was included because it is more computationally demanding, has a statistical basis according to the principle of ML, and is related to the ML method used in CFA.

These extracted factors were rotated three different ways: orthogonal varimax rotation, oblique promax rotation (Hendrickson & White, 1964) with the original varimax loadings transformed at powers of 2 (P2), 3 (P3), and 4 (P4), and the oblique Harris–Kaiser (HK) rotation (Hakstian & Abell, 1974; Harris & Kaiser, 1964) with the exponent parameter set at .00 (HK0), .25 (HK25), and .50 (HK50). These three methods were chosen because they represent three different classes of rotations. Varimax is probably the most widely used procedure, and it yields uncorrelated factors, though the factors obtained from virtually all confirmatory analyses include correlated factors. Promax yields correlated factors, but is based on an ad hoc method that transforms the original varimax factors. Harris–Kaiser is considerably more computationally demanding, and was derived directly for the purpose of oblique rotation. Because the oblique methods yield different results depending on the values of the corresponding but somewhat arbitrary parameters, a range of parameter values was chosen to evaluate each of the oblique rotations.

RESULTS

Two types of analysis were performed for this article. The purpose of EFA as a precursor to CFA is to recover the form of the model, with a subsequent CFA to provide parameter estimation. Accordingly, the most basic analysis in this article is how well the different combinations of EFA extraction and rotation recover the form of the underlying correct model. The analysis of the accuracy of the EFA estimates is also presented.

Recovery of Model Form

With the analysis of each sample correlation matrix, a SAS program written for this task assigned each indicator to the factor with which the indicator had the highest pattern coefficient. Table 1 lists the proportion of samples in each cell of the design in which all indicators were correctly classified; that is, in which each EFA extraction–rotation combination recovered the correct qualitative form of the model. The specified design outlined in this table included samples from the six cells (populations) defined by a factorial combination of sample size and factor correlation for the synthetic model, and two cells corresponding to sample size alone for the impulsivity model.

Unfortunately, a formal categorical modeling analysis of these proportions, in terms of a linear model analogous to analysis of variance, is not practical because of the large number of response categories relative to the amount and distribution of the data. The combination of 2 extraction methods and 7 rotation methods resulted in 14 repeated measures response categories for each sample correlation matrix. The response profile corresponding to each set of this sample data consisted of a string of 14 1s and 0s—a value of 1 if the corresponding combination of extraction and rotation successfully captured the form of the model, and a 0 if it did not.

The dispersion of response profiles was too heterogeneous to meet the assumptions required by categorical modeling (Freeman, 1987). For example, for the Synthetic .3 model at S = 100, only six of these profiles described more than one sample. Further, two of the profiles—all 14 analyses successful or all 14 analyses not successful—described 72 of the 100 samples. Accordingly, categorical modeling was not implemented, so the following trends are discussed at a descriptive level.

TABLE 1
Proportion of Samples with 100% of the Indicators Correctly Classified

Size	Factor Correlation	Extraction	Rotation							
			Varimax	*HK0*	*HK25*	*HK5*	*PM2*	*PM3*	*PM4*	*M*
Model: Synthetic[a]										
100	.2	PF	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		ML	.98	.99	.99	.99	1.00	1.00	1.00	.99
100	.6	PF	.69	.69	.71	.73	.72	1.00	.74	.75
		ML	.72	.72	.76	.76	.75	.75	.74	.74
100	.8	PF	.09	.11	.11	.73	.72	.72	.74	.46
		ML	.14	.14	.17	.76	.75	.75	.74	.49
300	.2	PF	1.00	1.00	1.00	1.00	1.00	100	1.00	1.00
		ML	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
300	.6	PF	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		ML	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
300	.8	PF	.60	.69	.68	.73	.68	.68	.69	.68
		ML	.77	.83	.85	.85	.82	.85	.83	.83
Model: Impulsivity[b]										
100		PF	.27	.21	.30	.34	.28	.31	.34	.29
		ML	.20	.20	.24	.24	.20	.20	.20	.21
300		PF	.99	.98	.99	.99	.99	.99	.99	.99
		ML	.98	.97	.97	.98	.98	.96	.96	.97

Note. PF = principal factors; ML = maximum likelihood.
[a]Model has 16 indicators. [b]Model has 44 indicators.

As expected, recovery of the form of the underlying model improved substantially as sample size increased from 100 to 300. More interesting is the interaction of sample size (S) and factor correlation (FC) for the synthetic model. For FC = .6 and S = 100, the mean proportion across all seven rotations of successful recovery for PF and ML were .75 and .74, respectively. These values both increased to 1.00 for S = 300. For the Synthetic .8 model at S = 100, complete recovery rates of only .46 and .49 for PF and ML were obtained, respectively, with an increase to .68 and .83 at S = 300. That is, relatively large sample sizes lead to excellent recovery rates, but a low sample size coupled with high factor correlations mitigates complete recovery of the model.

Table 2 demonstrates that although complete recovery is poor for some cells in the design, the samples in most cells had more than 98% of all indicators correctly classified. Even for the worst performing cell, the Synthetic .8 model at S = 100, most of the indicators were correctly classified: .79 for PF and .83 for ML when averaged over the seven rotational methods. The other Synthetic cells with less than 98% of all indicators correctly classified were the Synthetic .6 at S = 100 and the Synthetic .8 at S = 300. In both cases, 97% or more of all indicators were correctly classified. The only other cell with less than 98% of all indicators correctly classified was for the

TABLE 2
Proportion of Correctly Classified Indicators for Those Populations With Less Than 75% of the Samples Achieving Completely Correct Classification

Size	Factor Correlation	Extraction	Rotation							
			Varimax	*HK0*	*HK25*	*HK5*	*PM2*	*PM3*	*PM4*	*M*
Model: Synthetic[a]										
100	.6	PF	.98	.98	.98	.98	.98	.98	.98	.98
		ML	.98	.98	.98	.98	.98	.98	.98	.98
100	.8	PF	.79	.77	.78	.80	.80	.81	.80	.79
		ML	.82	.82	.84	.85	.83	.83	.83	.83
300	.8	PF	.97	.97	.97	.98	.97	.97	.97	.97
		ML	.98	.99	.99	.99	.99	.99	.99	.99
Model: Impulsivity[b]										
100		PF	.94	.94	.95	.95	.94	.95	.95	.95
		ML	.93	.94	.94	.94	.93	.94	.94	.94

Note. PF = principal factors; ML = maximum likelihood.
[a]Model has 16 indicators. [b]Model has 44 indicators.

Impulsivity model at S = 100, in which approximately 94% of all indicators were correctly classified.

For the factor extraction methods, ML performed about the same as PF for the synthetic model at the lower factor correlations, and slightly better than PF at higher factor correlations. For example, as reported in Table 1, for the Synthetic .2 model at S = 100, 100% of all samples with PF extraction completely recovered the model, a value that was 99% for ML extraction. This pattern reversed itself for the Impulsivity model. Here, for example at S = 100, the PF recovery rate was 29% compared to 21% for ML.

The factor rotation method did not have a practical effect on the recovery rate. No apparent pattern characterized model recovery in terms of rotation method. That is, the orthogonal varimax rotation did as well or as poorly as the six more sophisticated and presumably more appropriate oblique rotations included in these analyses. Only in the case of extremely high factor correlations of .8 did varimax not perform as well as the oblique rotation.

Recovery of Parameter Estimates

The other analysis concerned the accuracy of the parameter estimates for those indicators correctly assigned. The parameter-deviated data were analyzed in two different forms. The absolute value of the parameter-deviated values reflects the magnitude of sampling error encountered by the substantive researcher in a similar model-sample size situation. The square root of the sum of squared deviates for all indicators of a specific model (the root mean squared residual) is widely used to analyze the performance of an estimation procedure. Because the pattern of results was similar for both dependent variables, the results are reported only for the magnitude of the parameter-deviated values. Indicators assigned to the incorrect factor were treated as missing data.

Repeated-measures ANOVA of the parameter-deviated values for the four synthetic models and then of the two impulsivity models indicated that all the between-group main effects were significant: S and FC for the synthetic model ($F = 443.78$; $df = 1, 594$; $p < .01$ and $F = 2326.57$; $df = 2, 594$; $p < .01$, respectively) and sample size for the impulsivity model ($F = 966.15$; $df = 1, 198$; $p < .01$). As can be seen from the mean magnitude of parameter-deviated estimates reported in Table 3, the larger sample size almost halved the average amount of deviation of the estimate from the population value. Also, lower factor correlations lead to more accurate EFA estimates. For example, for the Synthetic .2 model, at S = 300, the mean magnitude of the parameter-deviated estimates averaged across all seven rotations was .034 and .033, respectively, for PF and ML, compared to the corresponding estimates of .072 and .072 for the Synthetic .6 model at S = 300 and .143 and .143 for the Synthetic .8 model at S = 300.

In terms of the repeated measures effects, the extraction and rotation methods were significant for both the analysis of the synthetic models ($F =$

TABLE 3
Mean Magnitude of Parameter-Deviated Estimates for Exploratory Factor Analysis and Confirmatory Factor Analysis (CFA)

			Rotation								
Size	*Factor Correlation*	*Extraction*	*Varimax*	*HK0*	*HK25*	*HK5*	*PM2*	*PM3*	*PM4*	*M*	*CFA*
Model: Synthetic[a]											
100	.2	PF	.056	.060	.059	.059	.059	.059	.059	.059	.053
		ML	.056	.058	.058	.058	.059	.059	.060	.058	
100	.6	PF	.094	.101	.104	.112	.108	.101	.100	.103	.049
		ML	.094	.102	.106	.111	.109	.101	.100	.103	
100	.8	PF	.150	.180	.178	.191	.189	.180	.181	.178	.049
		ML	.144	.164	.172	.179	.181	.169	.166	.168	
300	.2	PF	.033	.034	.034	.035	.034	.034	.034	.034	.030
		ML	.030	.034	.034	.034	.034	.034	.034	.033	
300	.6	PF	.079	.056	.074	.096	.084	.061	.057	.072	.028
		ML	.078	.057	.076	.096	.083	.060	.055	.072	
300	.8	PF	.144	.101	.138	.181	.179	.139	.116	.143	.027
		ML	.144	.105	.144	.182	.178	.136	.110	.143	
Model: Impulsivity[b]											
100		PF	.097	.112	.116	.121	.107	.104	.107	.109	.054
		ML	.107	.123	.126	.126	.119	.118	.121	.120	
300		PF	.077	.060	.075	.091	.077	.062	.059	.072	.030
		ML	.082	.068	.085	.096	.083	.069	.066	.078	

Note. PF = principal factors; ML = maximum likelihood.
[a]Model has 16 indicators. [b]Model has 44 indicators.

11.42; $df = 1, 594$; $p < .08$, and $F = 785.46$; $df = 6, 3564$; $p < .01$, respectively) and the analysis of the impulsivity model ($F = 56.58$; $df = 1, 198$; $p < .01$, and $F = 642.95$; $df = 6, 1188$; $p < .01$, respectively), as were many of the associated interactions. The size of these within-group differences were not as pronounced as for the between-group differences. One unexpected finding, however, is that the orthogonal varimax rotation generally outperformed the oblique Harris–Kaiser and promax rotations in five of the eight cells, the exceptions being the impulsivity model at S = 300, and the Synthetic .6 and .8 at S = 300. For example, for the Synthetic .6 model with S = 100, the average magnitude of error for CFA was .049. For varimax rotation of the principal axes factors, this value rose to .094, but varied from .100 to .112 for the Harris–Kaiser and promax rotations.

For the Synthetic .2 model, at S = 300, the accuracy of the EFA estimates almost equaled that of the CFA estimates, for which the parameter-deviated estimates had a mean magnitude of .030. The PF average across the seven rotations is .034 and the ML average is .033. The mean parameter-deviated estimates of the best rotation method in this situation, varimax, were only .03 higher for PF and equal for ML than the corresponding mean CFA estimates. For low factor correlations of .2 and a moderate sample size of 300, little difference is obtained in the accuracy of precision between the disparate estimation methods of EFA with the orthogonal varimax rotation and maximum likelihood CFA.

Finally, the size of the population indicator pattern coefficients was not related to the size of the estimation error in EFA. For example, consider the impulsivity model with PF extraction and varimax rotation at S = 300. The magnitude of the parameter-deviated estimates was examined in a design in which the 44 indicators were nested within their respective factors with 100 replications for each indicator. One missing value occurred for the 4,400 observations. Main effects for factors ($F = 20.43$; $df = 1, 13$; $p < .01$) and indicators ($F = 12.70$; $df = 1, 30$; $p < .01$) were significant. However, the percentage of total variance estimates, 41.4% and 6.1% for the factor and indicator effects, respectively, indicate the relative lack of importance of the indicator effect. To illustrate, the mean of the 100 estimates for each of the three indicators of the fifth factor were all identical at .04, and the mean estimates for each of the three indicators of the eighth factor were different in size from the fifth factor indicators, but similar to each other in values .15, .12, and .12.

Instead of the size of the pattern coefficient, the size of the factor correlations appear to be meaningfully related to the magnitude of estimation error—a result consistent with the previous discussion of factor correlations for the synthetic models in which the factor correlations were uniformly high (.6) or uniformly low (.3) for all factors in the model. To analyze this relation, the average correlation of each impulsivity factor with all other factors was computed. This value was then correlated with the average error for all of the indicators of the factor. The indicators of those factors that correlated more highly with other factors tended to have higher estimation errors than the indicators of factors that had lower factor correlations ($r = .32$).

DISCUSSION

Most uses of "confirmatory" factor analyses are, in actuality, partly exploratory and partly confirmatory in that the resultant model is derived in part from theory and in part from a respecification based on the analysis of model fit. A common practice is to use information provided from a CFA such as modification indexes and standard errors to incrementally respecify a model so as to obtain improved fit (thereby changing the reported standard errors and statistical fit of the model from formal statistical statements to only heuristic guides of fit). This article provides guidance to the substantive researcher regarding the effectiveness of an alternate heuristic strategy for data-driven model specification. Specifically, how effective is EFA in uncovering the structure of a measurement model?

This study examined 14 versions of EFA derived from a factorial combination of two types of extraction (PF and ML) and seven rotations (varimax; promax with powers of 2, 3, and 4; and Harris–Kaiser with values of the exponent parameter set at 0, .25, and .5). All these exploratory methods fared well in recovering the model except in small sample sizes with relatively highly correlated factors, and even in those situations most of the indicators were correctly assigned to the factors. The size of the indicator pattern coefficients did not meaningfully affect the magnitude of the estimation error, but larger factor correlations tended toward larger errors of estimation for the indicators of that factor.

Little differences exist between these 14 extraction–rotation combinations in the recovery of the structure of the model; generally, when one version worked well, so did the others. The surprise is that, except in the model with extremely high factor correlations of .8, the orthogonal varimax rotation did as well as the more sophisticated oblique rotations in recovering the model, and generally yielded more accurate estimates. One conclusion of this article is that for the purpose of building multiple-indicator measurement models in which the criterion is model validation with CFA, the sophistication and apparent greater appropriateness of the oblique rotations offered no comparative advantage over the simpler orthogonal varimax procedure.

The most general conclusion of this article is that EFA is a useful tool to aid the researcher in recovering an underlying measurement model that can then be evaluated with CFA. CFA of a model developed in part with EFA is a viable strategy for theory development and analysis. Of course, ultimately the model should be cross-validated on new data, but this cross-validation is needed in any program of theory development, including for any model that is respecified on the basis of fit information from a CFA program.

These results encourage the further development of a comprehensive research paradigm that exploits the relative and complementary strengths of so-called exploratory and confirmatory procedures along an integrated continuum of model specification, revision, and formal evaluation. This process culminates rather than begins with a ML structural equation analysis. Related research provides guidance on the use of very simple estimation procedures for CFA, such as the surprisingly successful Iterated Centroid Estimation procedure discussed by Gerbing and Hamilton (1994). Other research includes how and when measurement and structural models should be analyzed separately or simultaneously (Anderson & Gerbing, 1988) and how to address the number of factors problem-consistent from the perspective of CFA instead of EFA. The role of this study was the demonstration that exploratory factor analysis, particularly with varimax rotation of principal axes factors, appears to provide a useful heuristic tool for constructing multiple-indicator measurement models as a precursor to CFA procedures.

REFERENCES

Anderson, J. C., & Gerbing, D. W. (1982). Some methods for respecifying measurement models to obtain unidimensional construct measurement. *Journal of Marketing Research, 19*, 453–460.

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation models in practice: A review and recommended two-step approach. *Psychological Bulletin, 103*, 411–423.

Bentler, P. M. (1985). *Theory and implementation of EQS: A structural equations program.* Los Angeles: BMDP Statistical Software.

Freeman, D. H. (1987). *Applied categorical data analysis.* New York: Marcel Dekker.

Gerbing, D. W., Ahadi, S. A., & Patton, J. H. (1987). Toward a definition of impulsivity: Components across behavioral and self-report domains. *Multivariate Behavioral Research, 22*, 357–379.

Gerbing, D. W., & Hamilton, J. G. (1994). The surprising viability of a simple alternate estimation procedure for the construction of large-scale structural equation measurement models. *Structural Equation Modeling, 1*, 103–115.

Gerbing, D. W., Hamilton, J. G., & Freeman, E. (1994). The influence of management participation on organizational planning benefits. *Journal of Management, 20*, 859–885.

Hakstian, A. R., & Abell, R. A. (1974). A further comparison of oblique factor transformation methods. *Psychometrika, 39*, 429–444.

Hakstian, A. R., Rogers, W. T., & Cattell, R. B. (1982). The behavior of number-of-factors rules with simulated data. *Multivariate Behavioral Research, 17*, 193–219.

Harman, H. H. (1976). *Modern factor analysis* (3rd ed.). Chicago: University of Chicago Press.

Harris, C. W., & Kaiser, H. F. (1964). Oblique factor analytic solutions for rotation to oblique simple structure. *Psychometrika, 29*, 347–362.

Hendrickson, A. E., & White, P. O. (1964). PROMAX: A quick method for rotation to oblique simple structure. *British Journal of Statistical Psychology, 17*, 65–70.

Hunter, J. E. (1973). Methods for recording the correlation matrix to facilitate visual inspection and preliminary cluster analysis. *Journal of Educational Measurement, 10*, 51–61.

IMSL. (1980). *International mathematical and statistical libraries.* Houston, TX: IMSL.

Jöreskog, K. G., & Sörbom, D. (1989). *LISREL VII user's reference guide.* Chicago: SPSS.

Mulaik, S. A. (1972). *The foundations of factor analysis.* New York: McGraw-Hill.

SAS Institute Inc. (1989). *SAS/STAT user's guide* (Version 6, 4th ed., Vol. 1). Cary, NC: Author.

Thurstone, L. L. (1931). Multiple factor analysis. *Psychological Review, 38*, 406–427.